

**DEVELOPMENT OF DECENTRALIZED DATA
FUSION ALGORITHM WITH OPTIMIZED
KALMAN FILTER**

SAYED ABULHASAN QUADRI

UNIVERSITI SAINS MALAYSIA

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**DEVELOPMENT OF DECENTRALIZED DATA FUSION ALGORITHM
WITH OPTIMIZED KALMAN FILTER**

by

SAYED ABULHASAN QUADRI

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LIST OF SYMBOLS

CO	Carbon monoxide
CO ₂	Carbon dioxide
ej -	a priori error
ej	a posteriori error
F	Faraday
Hz	Hertz
I_0	Bessel function
m	Meter
mm	Millimeter
μ	Micro
mg	Milligram
m ³	cubic meter
Psi	Specific variance
R	Rényi entropy
r	Radius
s	Second
t	Time
	Loading matrix
	Ohm
	Variance

LIST OF ABBREVIATIONS

AAR	Alkali-aggregate reaction
ALV	Autonomous land vehicles
ANN	Artificial neural network
AQE	Air quality emergency
ARF	Almost ready to fly
ARM	Adaptive recursive model
BDDF	Bayesian decentralized data fusion
CC	Correlation coefficient
CCD	Charge coupled device
CSV	Comma separated values
DoD	Department of defence
EEPROM	Electrically erasable programmable read-only memory
EKF	Extended Kalman filter
EM	Expectation maximization
FA	Factor analysis
FEA	Finite element analysis
FPM	Fusion performance model
GIHS-GA	Generalized intensity-hue-saturation-genetic algorithm
GMM	Gaussian Mixture Models
IF	Image fidelity
IMU	Inertial measurement unit
KF	Kalman filter
LDA	Local Discriminant Analysis
LiPo	Lithium-Polymer

LOC	Lines of codes
LVDT	Linear variable displacement transformer
MEMS	Micro electro mechanical systems
MLP	Multi-layer perceptron
MPN	Most probable number
MRA	Multi-resolution analysis
MSDF	Multisensor data fusion
NBRI	National Building Research Institute
OA	Observed accuracy
OMI	Ozone monitoring instrument
PCA	Principal Component analysis
PCB	Printed circuit board
PDF	Probability density function
PLSE	Pseudo least squares estimates
PMLE	Pseudo maximum likelihood estimates
PNN	Probabilistic neural network
PSNR	Peak signal to noise Ratio
RCC	Reinforced cement concrete
RMSE	Root mean square deviations
SA	Situational awareness
SD	Standard deviation
SF	Spatial frequency
SHM	Structural health monitoring

PEMBANGUNAN ALGORITMA GABUNGAN DATA TERNYAHPUSAT DENGAN PENAPIS KALMAN TEROPTIMUM

ABSTRAK

Manfaat positif teknik penggabungan data telah mempengaruhi beberapa aplikasi kejuruteraan untuk melaksanakan teknologi tersebut. Walau bagaimanapun, terdapat beberapa cabaran yang masih perlu diatasi seperti pemilihan algoritma yang bersesuaian, kelewatan pemprosesan dan masalah jejalan memori. Tesis ini mencadangkan satu model penggabungan data yang akan memudahkan proses pemilihan algoritma selain mengoptimumkan jumlah pemilihan algoritma yang berpotensi. Model ini menggabungkan teknologi penggabungan data dengan domain kejuruteraan algoritma, dan dengan itu mengoptimumkan algoritma penggabungan data menggunakan teknik yang canggih seperti pengaturcaraan berfungsi untuk mengurangkan langkah pemprosesan dan penggunaan memori. Model ini direalisasikan dalam empat aplikasi penggabungan data seperti sistem unit pengukuran inersia (IMU), sistem OktoKopter, penggabungan data satelit dan penilaian struktur konkrit. Bagi keseluruhan aplikasi pelbagai penggabungan data algoritma seperti algoritma turas Kalman, algoritma faktor analisis (FA) dan pengusulan algoritma QR-FA telah dibandingkan dalam jangkaan kesalahan asas. Algoritma QR-FA yang dicadangkan telah dibangunkan dengan memperkenalkan beberapa langkah tambahan algoritma penguraian QR ke dalam algoritma piawai analisis faktor. Algoritma dengan paling kurang jangkaan kesalahan akan dipilih bagi proses pengoptimuman. Hasil keputusan bagi semua aplikasi mengesahkan bahawa pengoptimuman telah mengurangkan masa pelaksanaan dan penggunaan memori bagi penggabungan data algoritma.

DEVELOPMENT OF DECENTRALIZED DATA FUSION ALGORITHM WITH OPTIMIZED KALMAN FILTER

ABSTRACT

The positive virtues of data fusion technique have influenced several engineering applications to implement the technology. However, a number of challenges remain to be addressed, such as selection of appropriate algorithm, processing delay and bottleneck-memory problem. This thesis proposes a data fusion model that facilitates selection of algorithm and recommends selected algorithm to be optimized. The model collaborates data fusion technology with algorithm engineering domain, accordingly data fusion algorithm is optimized using sophisticated technique such as functional programming to reduce the processing delay and memory usage. The model is realized in four data fusion applications such as inertial measurement unit (IMU) system, OktoKopter system, satellite data fusion and concrete structure evaluation. In all the applications, various data fusion algorithms such as Kalman filter algorithm, factor analysis (FA) algorithm and the proposed QR-FA algorithm are compared on basis of estimation error. The proposed QR-FA algorithm is developed by introducing additional step of QR decomposition in the standard factor analysis algorithm. The algorithm with the least estimation error is selected for optimization. The results in all the applications confirm that optimization has significantly reduced execution time and memory usage of selected data fusion algorithm.

CHAPTER ONE

INTRODUCTION

1.1 General introduction

In the present era of technology, for many systems that require acquisition, processing and integration of information provided by several knowledge sources, the need for a mechanism that can transform incomplete, inconsistent or imprecise data provided by one sensor to more useful information by fusing it with data provided by other sensors is a crucial element to achieve autonomy and efficiency through machine intelligence. The area of data fusion provides solutions to problems that are characterized by intensive and diverse sensor information.

Data fusion is a general term that encompasses multifaceted and multilevel processing and deals with the association, correlation, automatic detection, approximate estimation and amalgamation of data and information from single and multiple sources to accomplish better refined estimates, and provide comprehensive and appropriate assessments of threats and situations and their impact (Data fusion lexicon, 1991).

The technology of data fusion handles synergistic arrangement of information obtained by various information sources, measurement sensor devices and decision makers. Thus, the process of sensor fusion is entirely concerned regarding identification of target, registration of sensors, distributed detection, decision-making and management of database. It utilizes diverse set of techniques/methods namely,

Bayesian method, method of least squares, Dempster–Shafer’s scheme, Fuzzy logic and artificial neural networks (Kokar and Kim, 1993).

1.2 Research motivation

Application of data fusion technology has enabled a higher performance primarily in terms of resolution and dynamics in various control-engineering applications. Multi-sensor data fusion providing reliable navigation information, and better state estimates established reputable position in many UAV applications. Fusion algorithms associated with noise filters incorporated at circuit design level have become indispensable part of many embedded control applications (Ridley, 2014).

In the geospatial domain, data fusion is often synonymous with data integration. Fusion centers facilitate the collection, analysis, and dissemination of hazard-related data (Stankut and Asche, 2009). In many complicated applications marine animal researchers use data fusion to combine animal tracking data with bathymetric, meteorological, sea surface temperature (SST) and animal habitat data to examine and understand habitat utilization and animal behavior in reaction to external forces such as weather or water temperature (Fekas et al., 2012). Data fusion has established a remarkable position in road and traffic safety applications. The data from the different sensing technologies can be combined in intelligent ways to determine the traffic state accurately. Fusion based approach utilizes data collected from roadside utilizing acoustic and image sensors (Joshi et al., 2013).

Multisensor data fusion by improving accuracy and precision has established significant advantages in various engineering applications. In order to convince growing demands pertaining to requisites of applications, new models, systems and algorithms are continually being designed and developed.